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DB = USPT, H	PGPB,JPAB,EPAB,DWPI,TDBD; PLUR=YES; OP=ADJ		
<u>L6</u>	6363333.uref.	. 1	<u>L6</u>
<u>L5</u> ·	L4 and (time adj5 interval\$1)	0	<u>L5</u>
<u>L4</u>	(time and stock and market\$).ti.	21	<u>L4</u>
<u>L3</u>	(interval\$ and track\$ and financi\$).ti.	0	<u>L3</u>
<u>L2</u>	L1 and time	1	<u>L2</u>
<u>L1</u>	(interval\$ and financial and data\$).ti.	3	<u>L1</u>

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Set Name side by side	Query	Hit Count	Set Name result set			
DB=USPT,PGPB,JPAB,EPAB,DWPI,TDBD; PLUR=YES; OP=ADJ						
L26	5671363.uref.	17	L26			
L25	5671363.pn.	2	·L25			
L24	(stock\$1 and trad\$ and database\$).ti.	4	L24			
L23	(stock\$1 and trad\$ and sql).ti.	0	L23			
L22	5946666.pn.	2	L22			
L21	(stock\$1 and market\$ and analysis).ti.	17	L21			
L20	6199077.pn.	2	L20			
L19 .	L17 and (dynamic near5 updat\$)	4	L19			
L18	L17 and (stock nar5 table\$1)	0	L18			
L17	L16 and (stock near5 track\$)	24	L17			
L16	L15 and (stock near5 symbol\$1)	201	L16			
L15	stock near5 market\$	3463	L15			
L14	(stocks and securities and track\$).ti.	1	L14			
L13	(stocks and securities and trend\$) ti.	0	L13			
L12	(stocks and securities and real and time).ti.	3	L12			
L11	(time and serie\$ and financial and data\$) ti.	2	L11			
L10	L9 and (interval near5 database\$)	3	L10			
L9	L8 and (stock near5 database\$)	57	L9			
L8	(financial near5 database\$)	1688	L8			
L7	(stock and market\$ and real and time) ti.	6	L7			
L6	L5 and (time near5 interval\$1)	1	L6			
L5	raw financial data	13	L5			
L4	L3 and (query\$ or search\$)	6	L4			
L3	11 and (time adj5 interval\$1)	22	L3			
L2	time interval data tables	1	L2			
L1	raw data tables	79	L1			

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Set Name	Query	Hit Count	
side by side			result set
DB = US	PT,PGPB,JPAB,EPAB,DWPI,TDBD; PLUR=YES; OP=ADJ		
L10	L9 and (financial near5 markets)	. 0	L10
L9	((plurality near5 intervals) same (adj\$ near5 data))	67	L9
L8	L7 and ((plurality near5 intervals) same (adj\$ near5 data))	0	L8
L7	(financial and market\$).ti.	183	L7
L6	5161103 uref.	15	L6
L5	L4 and (time near5 interval\$1)	7	L5
L4	(time near5 vary\$) same (stock near5 data\$)	12	L4
L3	L1 and (real near5 time)	. 3	L3
L2	L1 and ((time near5 vary\$) same (volume near5 data))	0	L2
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Parallel and Distributed Search for Structure in.. - Oates, Schmill, Cohen (1996) (Correct) (2 citations) Distributed Search for Structure in Multivariate Time Series Tim Oates, Matthew D. Schmill and Paul R. Search for Structure in Multivariate Time Series Tim Oates, Matthew D. Schmill and Paul R. Cohen as those describing the ebb and flow of the stock market or the health of a patient in an intensive care www-eksl.cs.umass.edu/papers/Oates96a.ps

Investigation of Periodic Time Series using Neural Networks.. - Gregory Noone (1995) (Correct) (1 citation) Investigation of Periodic Time Series using Neural Networks and Adaptive Error www.crasys.anu.edu.au/PTP/Projects/pulseTrain/Projects/pulseTrain/Projects/pulseTrain/Papers/../Papers/NH95b.ps

Transionospheric Signal Detection with Chirped Wavelets - Doser, Dunham (Correct) utilized to detect dispersed signals in the joint time/scale domain. Specifically, pulses that become discrete wavelet transform, applied to actual time series recorded by the US Department of Energy's www.utdallas.edu/~doser/as97paper.ps

A Neighborhood Map of Competing One Step Predictors for.. - Fancourt, Principe (Correct) for Piecewise Segmentation and Identification of Time Series Craig L. Fancourt and Jose C. Principe Piecewise Segmentation and Identification of Time Series Craig L. Fancourt and Jose C. Principe www.cnel.ufl.edu/bib/papers/fancourt96icnn.ps.gz

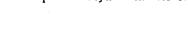
Markov Switching Time Series Models with Application to a.. - Lu, Berliner (1999) (Correct) (2 citations) Markov Switching Time Series Models with Application to a Daily Runoff Markov Switching Time Series Models with Application to a Daily Runoff Series www.cgd.ucar.edu/stats/papers/lu_berliner.ps.Z

Radar Pulse Train Parameter Estimation and Tracking using.. - Greg Noone (1995) (Correct) network is used based on a simple state space time series formulation of the radar problem. The network is used based on a simple state space time series formulation of the radar problem. The network chaotic analytic functions as well as some "stock-market" type problems [1, 2]Time series network www.crasvs.anu.edu.au/PTP/Projects/pulseTrain/Projects/pulseTrain/Papers/../Papers/Noo95.ps.gz

A Componentized Architecture for Dynamic Electronic Markets - Reich, Ben-Shaul (1998) (Correct) (2 citations) bids and asks are collected for a predetermined time interval and are matched at the end of the A Componentized Architecture for Dynamic Electronic Markets Benny Reich Israel Ben-Shaul Department of www.dsg.technion.ac.il/gem/papers/gem-sigmodrec.ps.gz

TREND: A System for Generating Intelligent Descriptions of .. - Sarah Boyd (1998) (Correct) (1 citation) A System for Generating Intelligent Descriptions of Time-Series Data Sarah Boyd Microsoft Research for Generating Intelligent Descriptions of Time-Series Data Sarah Boyd Microsoft Research Institute TREND: A System for Generating Intelligent Descriptions www.mri.mq.edu.au/~sarahb/icips.ps

Change of structure in financial time series, long range...- Mikosch, Starica (1999) (Correct) (2 citations) Change of structure in financial time series, long range dependence and the GARCH model www.cs.rug.nl/~eke/iwi/preprints/99-5-06.ps.gz



Modelling and robustness issues in Bayesian time series analysis - West (1995) (Correct)

Modelling and robustness issues in Bayesian time series analysis Mike West ISDS, Duke University,
Modelling and robustness issues in Bayesian time series analysis Mike West ISDS, Duke University,
ftp.stat.duke.edu/pub/WorkingPapers/95-12.ps

Flexible Seasonal Long Memory and Economic Time Series - Marius Ooms (1995) (Correct) (3 citations) Flexible seasonal long memory and economic **time series** Marius Ooms October 12, 1995 Econometric www.eur.nl/few/eb/papers/../pub/oomsart1.ps

<u>Graphical techniques for selecting variables for time series. - Marriott, Pettitt (Correct)</u>
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Neural Learning of Chaotic Dynamics: The Error.. - Rembrandt Bakker.. (1997) (Correct) (4 citations) to identify chaotic dynamics from a single measured **times**eries. The algorithm has four special features: 1. The state of the system is extracted from the **time-series** using delays, followed by weighted Principal www.neci.nj.nec.com/homepages/giles/papers/UMD-CS-TR-3843.neural.learning.chaotic.dynamics.ps.Z

Another Look At Swedish Business Cycles, 1861-1988 - Joakim Skalin, Timo Teräsvirta (1996) (Correct) (2 citations)

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similar (i.e. they react similarly to changing **market** conditions) even though one fluctuates near \$30 www.almaden.ibm.com/cs/quest/papers/cg97 expanded.ps

Evaluating Neural Network Predictors by Bootstrapping - LeBaron, Weigend (1994) (Correct) (6 citations) exhibit the method in the context of multi-variate **time series** prediction on financial data from the New the method in the context of multi-variate **time series** prediction on financial data from the New York held-out test set that includes the 1987 stock **market** crash. We also compare the performance of the wueconb.wusti.edu:8089/eps/fin/papers/9411/9411002.ps.gz

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Learning to Classify Sensor Data - Manganaris (1995) (Correct)

Data from sensors are usually made available over **time** and are classified according to the behavior they problem of classifying finite, univariate, **time series** that are governed by unknown deterministic www.vuse.vanderbilt.edu/~stefanos/stefa

<u>Conditional Minimum Volume Predictive Regions For Stochastic.. - Polonik, Yao (1999) (Correct)</u> by interval/region prediction in nonlinear **time series**, we propose a minimum volume predictor statlab.uni-heidelberg.de/pub/reports/by.series/report.15.ps

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